Aspects of Decision-Making in Human-Machine Teaming

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Abstract. In a digital world, joint decisions in decentralized infrastructures are increasingly necessary. Factors such as complexity and uncertainty characterize this decision-making playing field, as does a diversity of human and machine actors. Fast data-driven results can resolve decision-paralyzing uncertainties and, in combination with innovative approaches based on causality, make complexity manageable. Embedded in the principles of swarm intelligence of superorganisms, a joint decision-making process of human teams and data-driven machines receives the benefits of self-organization and emergence.

Keywords: Augmented Intelligence, Collective Intelligence, Decision Making, Human-Computer Interaction, Human-Machine Teaming, Sociotechnical Systems.

1 Joint Decision-Making

The structures of the network enable an exchange between diverse entities. In addition, artificial identities are enabled to calculate viable decisions or decision proposals through processes such as machine learning as well as constantly growing amounts of data. At the same time, new types of communities and interactive maneuvers are emerging in the digital infrastructure. Due to this growth in acceleration and complexity, the success of decision making as a single human actor becomes unnecessary or even impossible. Numerous aspects come into play in order to allow a decision-making process to emerge from complex dynamic initial situations, which balances the opposing strengths and weaknesses of all actors - human and artificial - in a self-organizing system and emerges to an optimal consensus.

1.1 Development of the Framework Conditions

When processes take place, choices often arise and a decision must be made. If no turn is actively made, this too is a decision: the decision to stay in the current process or to accept the end of the road, à la Buridan's donkey or Aesop's fox. So every action, whether conscious or unconscious, is always preceded by a decision.

The fact that the human brain makes a decision on average every four seconds as part of an implicit autonomic process shows that the ability and power to make decisions is of particular importance. Decision-making power has become indispensable due to various changes in people's living conditions, which are perceived as more complex and thus more challenging than a few decades ago due to a plethora of options [20]. This multi-optionality shapes both society as a whole and the individual. As homo optionis, entire life worlds are governed by decisions. Crucial to decision-making are the outcomes that occur both as triggers for decisions and as their consequences.

Being able to choose from a range of options is a gift of freedom that at the same time comes with a burden that should not be underestimated. The decision-making process as such is already a challenge as the dynamics and complexity of the initial situation increase. Moreover, a decision is inconceivable without responsibility for the resulting consequences.

In order to relieve the burden on the individual, decisions are increasingly being made collectively, thus sharing the burden of decision-making and responsibility. This was made possible by the softening of the social patriarchy, in which an individual had sole decision-making authority. But the basic democratic idea also plays a role in the development of joint decision-making, as does the desire of the individual to be able to contribute something to the decision. At the same time, democracy itself can be understood as a form of cooperation [31], which is necessary to reach a decision supported by all in a common struggle.

This upheaval in the framework of decision-making affects small communities such as families or teams, as well as larger groups from the entrepreneurial context or even entire masses, as they exist in the digital or political framework. At the same time, digitization and decentralization are creating more and more technical systems made up of numerous actors that also have to face the challenges of shared decision-making.

1.2 Communication

Due to complex problem situations and the associated abundance of tasks as well as a multitude of co-decision-makers, communication enables an optimal collaborative process. However, the bundle of experience, intuition and knowledge from the multitude of decision makers does not correspond to an addition of the contributed intelligence, which grows through communication and cooperation, but can exceed the actual sum many times over through emergence [14, 24].

Every aspect brought into a decision-making process encounters a diversity of expertise in a group that optimizes or enables insightful perception, interpretation and evaluation. If the tasks and roles within a group or project are tailored to the knowledge and skills of individuals, the achievable level of performance increases in addition to interdependence. This is a process exemplified in the animal kingdom, for example in groups, herds, flocks, or swarms [5, 28]. If one wants to focus on the communication and coordination of these natural systems in a model-like way, superorganisms as emergent organisms are exemplary [19, 34, 35].

Swarm intelligence as a subfield of artificial intelligence focuses its research on the actions of the individuals of a swarm or system. Decentralized systems consisting of numerous actors, so-called multi-agent systems, are characterized in particular by the fact that their natural or artificial actors communicate with each other, enabling cooperation and collaboration, which also influences the environment of these systems [44]. The inherent properties of these complex, decentralized systems, such as the aforementioned cooperation and coordination, as well as the influence of the actors involved and the external environment through sophisticated communication, offer numerous analogies for the sciences of digital communication and technical networks.

If one looks for natural systems that can be studied through their individual actors and that simultaneously combine autonomy, self-organization, and inherent shared decision-making in a distributed system, one comes across superorganisms such as honeybee colonies. However, even these natural systems struggle with the challenges of a complex dynamic environment in which optimal decisions have to be made under time-critical aspects.

1.3 Cooperation and Coordination

Natural systems, originally declared stupid, were taken for granted until proof of this assumed deficiency was refuted by the affected masses themselves [15]. A collective intelligence becomes possible, despite bounded rationality [39], through a common basis of deliberation for decisions. Furthermore, if a decision-making mass is coordinated, a symphony of emergently generated intelligence emerges from the cacophony of opinions, which can execute near-perfect decisions despite the limiting cognitive restrictions of individuals [43]. In addition to possible emergence, other characteristics crystallize in groups that require leadership through coordination. Surging emotions, contradictory behavior, manipulation, or even violence should be transformed into creative solutions to problems through purposeful channeling.

If a joint decision is sought, an open basic attitude and further skills of the participants are required for a successful process. These include, for example, attentive and conscious perception, the willingness to question one's own attitudes and patterns, to learn and to allow changes, as well as to communicate this inner process and the competence to endure the conflicts and tensions that arise in the process. If these prerequisites are not met by the decision-makers, the potential for conflict increases due to diversity and individual needs. In this respect, a joint decision or a consensus reached is an expression of a successful community of competent actors.

For the formation of a macro-decision while maintaining the independence of individual micro-decisions, a balancing cooperation within the framework of mutual dependencies is required. If cooperation as a carrier of a joint decision-making process ceases to exist, it must be replaced by coordination. If information is not exchanged between decision-makers, e.g. due to lack of communication or cooperation, the specific accumulated knowledge remains with each individual decision-maker and thus flows only minimally into the joint decision-making process. If, on the other hand, the individual's freedom of decision was to be restricted at the micro level by burgeoning group effects, the joint decision would be predetermined in favor of a selected option, despite the transfer of knowledge. The extent to which independent information in combination with collective communication can lead to optimal decision-making processes is shown by an agent-based model that simulates the nesting of swarms of honeybees. The interlocking of independence and interdependence between the individual agents of the model leads to excellent results of collective decision making [27].

1.4 Artificial Actor

The challenges of decision-making thus include not only the complexity of the initial situation, a collective decision-making process characterized by communication and cooperation, but also the task of coordination through an increasingly decentralized distribution of decision-makers. Achieving a collective decision requires more interaction than just sending and receiving signals. Consensus theory assumes constitutive bases to which the actors of a system are subjected and which drive them to reach a consensus. Thus, the very structure of communication within a system creates a pull that drives actors to reach consensus [17, 47] and is necessary for a collective [32]. For a collective decision making process in a system of human and artificial actors, this communication structure has to be created extra to generate a pull for consensus building. For example, by integrating principles and structures of the democratic decision-making process of superorganisms like honeybees [36]. But also the aspects: Communication, Complexity, Cooperation and Coordination do not form a complete picture of the challenges for collaborative decision making. In addition, there is another aspect: the artificial actor.

Artificial systems that support both micro and macro decisions are usually integrated into an existing architecture as middleware or business intelligence modules. For less complex decision bases or for sporadically used support by an artificial system, it can also be provided as Software as a Service (SaaS) [23]. These systems, often referred to as artificial intelligence, make decisions or provide decision recommendations based on extensive data analysis, e.g., by recognizing patterns, and thus use a data-driven approach to decision making. For the other aspects mentioned, additional specific software can provide further support, in favor of cooperation, communication and coordination.

2 Hybrid Joint Decision-Making

If we look at the decision-making processes of natural persons or collectives and compare them with the approach of artificial actors, such as machine learning (ML) algorithms, fundamental differences become apparent. An artificial actor will calculate a decision based on mathematical rules, in which a set of variables is used as input and a calculated prediction is compared with a targeted goal. Natural actors, on the other hand, resort to a mix of variants. For this purpose, different heuristics are combined with static procedures and implicit knowledge.

In the context of cognitive research on collective intelligence, online coordinated crowds compete in various tests against artificial systems in the form of software programs, with the emerging natural crowd winning with a probability of almost 90%. If the problem to be solved changes from complicated to complex, this value varies between 60% and 70% [1, 29]. Background are the different tactics of decision making, from which again different kinds of errors can result. For example, human decision-making tactics have a weakness in the assessment of risks [13], whereas algorithms have a weakness in terms of robustness, which can be found in particular in increasing dynamics in the initial or data situation [10]. At the same time, it is possible for artificial actors to benefit from the feedback of natural experts, as demonstrated by decision making in a clinical context using reinforcement learning [22]. The approach of Interactive Machine Learning (IML) already starts with the integration of feedback during the modification of a ML model [2, 45]. A mutual complementing and balancing could enable an optimal decision making strategy. For this, the actors must be able to learn from each other through mutual cooperation and communication via a coordinating strategy. This resulted in a balancing of opposing strengths and weaknesses, which leads to the assumption that a symbiosis of humans and machines or human communities and artificial actors can lead to a joint decision - a kind of hybrid joint decision - that represents an optimal problem solution despite complex issues [4].

2.1 Stability

Numerous electronic control systems in everyday human scenarios show that cooperation between humans and machines based on the division of labor is possible. These hybrid teams can be found in diverse areas such as interaction with robotics (e.g., transportation, manufacturing, medicine), the coordination and task management of driving or flying machines (e.g., logistics, military), the Internet of Things (IoT) (industry, smart home), autonomous driving (mobility), or in decision support systems of industry-specific applications (management). Thus, in trivial scenarios, artificial, i.e. machine actors are often empowered to make decisions that were previously made by individuals. This trust in artificial agents, which has grown through experience, has grown in numerous everyday decision-making scenarios. For example, drivers of motor vehicles delegate decision-making authority, sometimes unconsciously, to numerous control devices such as the anti-lock braking system (ABS) or by consciously switching on an autopilot in the cockpit of an aircraft. The latter aims to transfer the experience of decisions made by human actors to artificial systems in order to make them usable for tactical tasks of coordination in air traffic [6].

Behind the decision-making capability of control units and other software controlled machines are numerous loops of conditions and associated options cast in program code. After receiving impulses about the situation, a predefined option can be selected in a fraction of a second and an action such as switching on the anti-lock braking system can be triggered by the control unit. The ECU takes the decision action from the driver and has implemented a proven and thus confidence-building heuristic with this trivial procedure [3]. In an unchanging decision situation with complete data sets on the initial situation, such a heuristic is sufficient. However, exceptions and thus wrong decisions occur in about twenty percent of all results of artificial agents [11]. Although a statistical probability can usually be given to what extent the calculated result is correct, this can quickly be very far off the mark in a nonlinear environment. How much extrapolations from the past can lead to wrong decisions is shown by the peak of the financial crisis in 2008. In the largest insolvency case in U.S. history up to that time, the investment bank Lehman Brothers and its subsidiary were still rated A+ by the rating agency Standard & Poors (S&P) three days before their demise [41]. Despite a variety of ways to control the training process of a machine learning model, e.g., using free parameters such as weights, no optimal decision or decision proposal is certain, even with careful preparation. However, the environments that are unfriendly for machines to learn and that constantly change the status quo are often the dynamic systems in which complex decision situations arise [12]. In the context of automated decision-making in autonomous driving or medicine, this is a risky game of trust. Mass data analytics and machine learning are not yet optimally equipped for the complexity of their decision space, and Laplace's demon [30] remains a castle in the air, although statistics has gained ground in recent decades.

2.2 Decision-Making Context

In new developments in artificial intelligence, the teaching of rules is abandoned and artificial systems are trained to recognize patterns based on data. Thus, the degree of decision-making competence depends on the quantity and quality of the training data. At the same time, the resulting basis for decision-making always remains past-related with partially contradictory information and uncertainties. In addition, despite the flood of information in many areas, there is a lack of data to enable artificial systems to make meaningful decisions. This includes, for example, image data of cancers inside the human body for pattern recognition of artificial actors [33].

In knowledge engineering (KE), which is also a subfield of artificial intelligence and develops knowledge-based systems, humans are imitated as decision makers by reasoning mechanisms and rules [38]. However, humans remain an intangible entity that remains unpredictable, e.g., due to epistemic transformative events or impermanent signals. Nevertheless, natural decision makers such as humans are able to create creative thought worlds based on their imagination that are not exclusively reproduced from the past or extrapolated from data. Another key aspect that allows the assumption that machine decision making in chaotically complex systems is subject to the capabilities of natural systems is the ability of humans to recognize and understand simple causalities that are hidden from the artificial decision maker. For example, the human decision maker is fully aware that not all people wearing jerseys and sneakers in a stadium are athletes. An artificial system is not automatically aware of this. If, on the other hand, the interaction increases in several dimensions due to the complexity of the situation to be decided, the human decision-maker quickly reaches his limits. Due to the constantly deepening interlocking of humans and machines and the associated joint decision-making, the optimal interlocking of the two components as a kind of Anthropology 4.0 is indispensable.

The stringent approach of an artificial actor and the emergence and creativity potential of natural systems also allow the assumption that a decision-making process can be optimally designed even under complex conditions if there is an approach for a symbiosis of human groups and artificial actors by means of intelligent tactics. Balancing the strengths and weaknesses of natural and artificial actors is recommended for optimal interaction of collective decision making in an uncertain, complex environment. The goal is to intertwine causality awareness and creativity at the human micro-level and collective intelligence at the macro-level, interwoven in a shared decision-making process while efficiently processing vast amounts of data of a linear process and intertwining within an effective framework of evolutionarily proven emergent and self-organized principles and structures of superorganisms.

2.3 Scientific Principles

Science has been dealing with the emerging phenomenon of complexity since the early 1950s and since then has been trying to understand it with the help of artificial intelligence, cybernetics, mathematics and systems theories [9]. The claim of cybernetics is to understand human and machine as elements of a self-controlling system. Since the 1980s, open dialogue in human-machine systems has also become a focus of interest [8]. Numerous scholars are already addressing the intersecting issues of complexity science and human-machine interconnections, which can grow into extraordinarily complex overall systems. The processes of hybrid collaborative decision making behind a conceptualization are themselves subject to rules and processes already recognized in psychology, sociology, and decision theory, which must be taken into account when devising a viable heuristic. Theories of reflexive modernization as well as network and systems theory or decision theory of economics as well as game theory of mathematics can be suppliers for functional links between natural and artificial systems. These theoretical foundations from the logic of joint decision-making are thus the building blocks on which a sustainable consensus can grow.

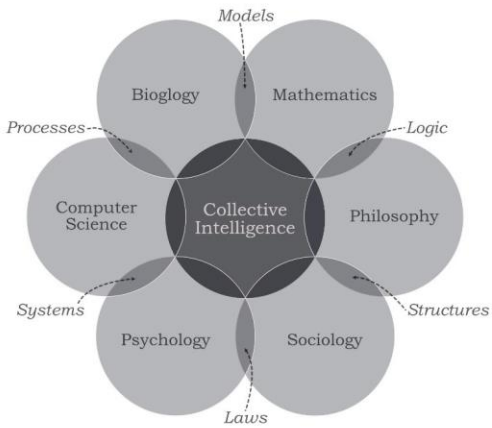

Fig. 1. Scientific disciplines and methods in favor of collective intelligence.

The unifying element of a possible decision-making concept can be philosophy and sociology to interweave different disciplines for collective intelligence (see Fig. 1), which enables a common structure like a fabric [16] of decision-making culture. A schematic representation of the disciplines involved in collective intelligence that enables consensus building, in the form of a rosette, illustrates the diversity of influencing factors. For example, due to the epistemological interest between mathematics and philosophy, logic (logicism) [37] can be used as an indispensable component for human-machine collaboration to foster consensus that can meet the quality requirements of diverse application scenarios. Another intersection in the description of collective intelligence is mathematics with biology, which can also be seen as a reason why numerous phenomena in biology are attempted to be fathomed with the help of algorithms and modeling. Examples are the tactics of ants for the shortest path in navigation, Evolutionary Computing (EC) as a generic term for numerous algorithms inspired by the bio-logical concept of evolution and used for global optimization, or Artificial New Networks (ANN) inspired by the network of neurons in the nervous system. Principles from nature have always been adopted and used to develop outstanding technical innovations.

3 Next Level of Optimal Decision-Making

For an interdisciplinary decision-making concept, it remains to be stated that for the framework conditions of human-machine decision-making the necessary tasks of communication, cooperation and coordination as well as a constant human-machine interaction or integration must be given. The fact that these tasks have gained relevance can be seen in the unpredictable complexity of the increasingly networked and thus larger decision-making environment, which leads to multi-optionality. Emergent and shared information bases that find their way through heterogeneous human-machine groups in an uncoordinated manner provide a breeding ground that must be navigated. Emotions sparked by information and behavior, burgeoning manipulations and attempts to influence through psychological or physical violence can act as a catalyst for creative problem solving under constraints.

Considering the limited rationality of human thinking and the existing uncertainty factor in the decision environment, there is usually an attempt to improve the information base [40]. This may result in the desire to cooperate with other decision makers. But also the desire to integrate artificial intelligence into the decision-making process, as it makes better decisions than humans when dealing with large amounts of data and linear processes. The possibility of connecting humans and machines as a team can form a new level in the competence of optimal joint decision making [42]. Using the principles of swarm intelligence, the causality and creativity accessible only to humans can enter an emergent decision-making process in a self-organized manner with the computations of artificial decision makers based on big data. Moreover, a principle-guided joint hybrid decision-making process can counteract the mere adoption of calculated opinions by artificial actors, as is partly the case, for example, in ChatGPT [26] or in clinical decision support systems (CDSS) [7].

To create an attraction that motivates the team of humans and machines to reach consensus [17], the principles of Superorganisms can be applied. In doing so, the strategic goals should be maintained, which are followed by both nature-inspired algorithms and the behavioral patterns of natural swarms known as intelligence: Effectiveness, Efficiency, Resource Conservation, Performance Optimization, Stability, Flexibility, Growth Capability and Scalability. The principle of self-organization is necessary for decentralized decision-making groups to successfully complete the process along the chosen path of subsidiarity. Virtual community thrives in an environment of operational decentralization, supported by digitalization and networked according to the principles of self-organization.

However, the interactive connection of hybrid human-machine decisions can hardly be evaluated on the basis of their demonstrable results. Decisions in complex dynamic systems proceed without counterfactuals in a productive environment. Although interrelationships can be visualized in near real time and impact assessments can be made, a fully computed forecast is not possible with them.

4 Conclusion

Through assessments in connection with pointing out acute currents, irrationalities, unconscious coexistences or linkages of the micro and macro level, awareness, perception and observation can be given space through visualization. Complexity gains influence through understanding, as individual aspects are brought into view without reduction. The opened field of vision, which is opened in a visualization of the current situation, is, however, a view of the calculated past, which at best has worked its way up to just behind the actual state and describes subjective action. The optimal embedding of the competences of natural and artificial systems in a dynamic, complex and decentralized structure can transform the status quo of the common decision culture of opposing polarities into interrelated units, a kind of anthropology 4.0, which enables to discuss a common optimal hybrid decision process. This is similar to the claim of cybernetics to create a system of self-organization, which as a hybrid balances the opposing strengths and weaknesses of human and machine in a common process [4]. In this context, the assumption of an anthropocentric mode is not appropriate, but rather the embedding of equal actors in a common hybrid system [18], which interacts as a unit, a kind of organism, and is thus jointly subject to the principles of its environment, such as complexity or acceleration. Based on a Digital Anthropology [25] as a research discipline originating from social anthropology, which analyzes human and machine systems in digital space by means of cybernetic views, this can be extended to an Anthropology 4.0. The background to this is, on the one hand, the obligatory approach of digital anthropology to holism [21], which is also essential in hybrid human-machine decision-making; on the other hand, the logic of the second eponym of Industry 4.0. Thus, the fundamentals of Industry 4.0: networking and intelligence in the form of interaction as well as the resulting autonomous self-control [46] are the clocks for raising hybrid decision-making to a new level.

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